Individualism, nationalism, ethnocentrism and authoritarianism

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Chapter 6
The relationships between Individualism, Nationalism, Ethnocentrism, and Authoritarianism in Flanders, analyzed in continuous time by means of the EDM/SEM Model

Some authors present evidence that nationalism (N) is not only related to individualism (I) and ethnocentrism (E) but also to authoritarianism (A). Therefore, we expand the nationalism-individualism-ethnocentrism model by Toharudin et al (2008) by including authoritarianism (A) as a fourth latent variable. A was measured by 7 items in two waves and 4 items in one wave giving a total of 18 observed variables measuring A which were added to the 48 variables measuring I, N, and E. We prove that the model is identified. By means of Mx the EDM solution for a model with drift coefficients, fixed growth intercepts, diffusion coefficients and initial parameters was estimated. We find rather strong reciprocal effects between A and E and also a relatively strong effect of A on I but no reverse effect from I to A. Whereas relatively small but significant effects from I and E on N are found, no effect is found from A on N. Autoregression functions, cross-lagged effect functions, and latent mean trajectory estimates and predictions are shown.

6.1 Introduction

The reciprocal relationships between the latent variables individualism (I), nationalism (N), and ethnocentrism (E) in the Flemish electorate have been studied by Toharudin et al., (2008), using the data set of the General Election Study (Interuniversitair Steunpunt Politieke-Opinieonderzoek, 1991, 1995, 1999). The rationale of the three variables model was the voting behavior in Flandres in favor of the extreme right-wing party Vlaams Blok, that fiercely fights for independence of Flanders. I, N, and E are often considered to be important elements of the party's extreme right-wing position. These variables were measured in three waves (1991, 1995, and 1999) in a panel of N = 1274 Flemish respondents and Dutch-speaking respondents in Brussels. The relationships between the variables were analyzed by Toharudin et al. (2008) in continuous time. See Oud & Delsing (2010) and Oud et al (2010) for the rationale of continuous time modeling.

Toharudin et al. (2008) found significant effects in both directions between I and E, with the standardized effect of I on E (0.039) being slightly stronger than in the opposite direction from E on I (0.033). Different from what was suggested in the literature, no significant effects from N on the two other variables were found. Instead, it turned out that both I and E had small but significant effects on N (standardized values of 0.013 and 0.011, respectively). On the basis of the continuous time parameters, the cross-lagged effects between the variables across a time interval of 60 years were calculated. In the feedback loop between I and E the I → E effect exceeded the E → I effect over all lags in the 60 year period with the maximum of I → E (0.235) occurring slightly later (after 17 years) than the maximum (0.190) of E → I (after 16.4 years). The rather persistent effects of both I and E on N had lower but still substantive maxima of 0.105 and 0.099, respectively, occurring only after 22 and 23 years. Finally, whereas the means of I and E hardly changed over the entire period considered (1991-2051), N showed quite some increase over the data collection period (1991-1999) with a further increase in the prediction period until about 2019.

Authoritarianism (A) is a form of social behavior characterized by strict obedience to the authority of the state or an organization and adherence to enforcing and maintaining control through the use of oppressive measures. In this paper we expand Toharudin's et al. (2008) model by adding A as an additional explanatory variable of N.

A is measured in each of the years 1991, 1995 and 1999 by seven items. Only two items were exactly the same in all three waves, however. In a series of congenericness tests, Toharudin et al. (in press) proved that all seven items used in 1991 and 1995 and four items used in 1999 can be considered to measure the same latent variable. Hence, the 18 observed variables, measuring A in the three waves, were added to the 48 variables measuring I, N, and E. In Toharudin et al. (2008) there were 51 variables measuring I, N, and E. However, we dropped the fifth item for I that in 1999 strongly differed from the measurement origin in

1991. So, the total model considered in the present paper comprises 66 observed variables and 12 latent state variables (I, N, E, A) in three waves.

Although I, N, E, and A have been the subject of several studies in Flanders, a longitudinal analysis of all four concepts and their relationships in continuous time has not been performed. Research by van Hiel and Miervelde (2007) shows strong positive correlations between A and a wide variety of indicators of right-wing ideology. In theoretical contributions by Tajfel (1982), Turner (1982), and Eisinga and Scheepers (1989) it is argued that A brings about E, while Scheepers et al (1992) found A to be an important predictor of E. In the present study we will first check whether the effects found in Toharudin et al. (2008) remain valid when A is added to the model, and next estimate and test the effects of A on all three variables I, N, and E and vice versa.

The paper is organized as follows. Section 2 summarizes the EDM/SEM model as given in Oud and Jansen (2000) and Oud and Delsing (2010). In section 3 we prove identification of this model with four latent state variables and three equally distant measurement time points. In section 4 the main results are presented. In addition to the customary z-tests of the effects by means of standard errors we will also perform likelihood tests. Furthermore, we will test whether the inclusion of "trait" variables (random intercept variables) improves the model. Finally, section 4 contains the conclusions.

6.2 The EDM/SEM model

Consider the following continuous time model:

$$\frac{\mathrm{d}\mathbf{x}(t)}{\mathrm{d}t} = \mathbf{A}\mathbf{x}(t) + \mathbf{b} + \boldsymbol{\kappa} + \mathbf{G}\frac{\mathrm{d}\mathbf{W}(t)}{\mathrm{d}t}, \tag{6.1}$$

$$\mathbf{y}_{t_i} = \mathbf{C}\mathbf{x}(t_i) + \mathbf{d} + \mathbf{v}_{t_i} \ . \tag{6.2}$$

It consists of a stochastic differential equation (6.1), describing the evolution of the latent variables in the n-vector $\mathbf{x}(t)$ (n = 4 in the present study) in continuous time, and a measurement equation (6.2) describing for all observed variables in vector $\mathbf{y}_{t_i}$ how the n latent state variables in continuous time are measured at the discrete observation time points $t_i (i = 1,...,T)$. T is the total number of observation time points (T = 3 in the present study). The number of elements in vector $\mathbf{y}_{t_i}$ may vary by observation time point, as in the present study (in 1991 and 1995 seven items were used to measure A, in 1999 only five).

The elements of $\mathbf{W}(t)$ are the Wiener process (see e.g., Arnold, 1974; Kuo, 2006). In addition to the Wiener process, which by definition is normally distributed, also the initial state variables in $\mathbf{x}(t_0)$ are assumed to be normally distributed, $\mathbf{x}(t_0) \sim N\left(\boldsymbol{\mu}_{x_{t_0}}, \boldsymbol{\Phi}_{x_{t_0}}\right)$, as well as the measurement errors, $\mathbf{v}_{t_i} \sim N\left(\mathbf{0}, \mathbf{R}_{t_i}\right)$. Drift matrix $\mathbf{A}$ (auto-effects on the diagonal and cross-effects off-diagonally) is analogous to the autoregression matrix (autoregressions on the diagonal and cross-lagged effects off-diagonally) in discrete time. The autoregression matrix between observation time points will be derived as a nonlinear function of the drift matrix and the observation interval.

Multiplied by matrix $\mathbf{G}$, the standard multivariate Wiener process $\mathbf{W}(t)$ with covariance matrix $\mathbf{I}$ at t = 1, is transformed into a more general Wiener process with covariance matrix $\mathbf{Q} = \mathbf{GG}'$ at t = 1 (Ruymgaard and Soong, 1984, pp. 68-75), called diffusion matrix. Analogously to the relation between discrete time autoregression matrix and drift matrix, the discrete time error covariance matrix is derived as a nonlinear function of the diffusion matrix, the drift matrix, and the observation interval.

The fixed intercepts $\mathbf{b} \neq \mathbf{0}$ accommodate nonzero mean trajectories $E[\mathbf{x}(t)]$. Particularly, $\mathbf{b} \neq \mathbf{0}$ defines the final nonzero means towards which a stable system eventually converges. Fixed intercepts $\mathbf{d} \neq \mathbf{0}$ in the measurement equation allow for different measurement origins of the observed variables.

The variables that make up the vector $\boldsymbol{\kappa}$ in the state equation (6.1) represent constant (over time) random intercept variables, $\boldsymbol{\kappa} \sim N\left(\mathbf{0}, \boldsymbol{\Phi}_{\kappa}\right)$. They are referred to as "trait" variables, represent unobserved heterogeneity between subjects and keep the subject trajectories apart. Note that the covariance matrix $\boldsymbol{\Phi}_{\kappa, x_{t_0}}$ between initial state and random intercept cannot, in general, be assumed zero, because $\boldsymbol{\kappa}$ is modeled to influence $\mathbf{x}(t)$ continuously, after but also already before t_0.

Oud & Jansen (2000) propose to estimate model (6.1)-(6.2) by means of the Exact Discrete Model (EDM). The EDM, introduced in 1961-1962 by Bergstrom (1988), links in an exact way the discrete-time model parameters to the underlying continuous-time model parameters by means of nonlinear constraints. The link is obtained by solving the stochastic differential equation in equation (6.1) for the observation intervals $\Delta t_i = t_i - t_{i-1}$ and relating the discrete time parameters in the discrete time equation (6.3) to the underlying ones in (6.1) by the highly nonlinear restrictions on the discrete time parameters, given in (6.4):

$$\mathbf{x}_{t_i} = \mathbf{A}_{\Delta t_i} \mathbf{x}_{t_i - \Delta t_i} + \mathbf{b}_{\Delta t_i} + \boldsymbol{\kappa}_{\Delta t_i} + \mathbf{w}_{t_i - \Delta t_i} \qquad \text{with } \operatorname{cov}(\mathbf{w}_{t_i - \Delta t_i}) = \tag{6.3}$$

The restrictions in (6.4) relate the autoregression matrix $\mathbf{A}_{\Delta t_i}$ to the drift matrix $\mathbf{A}$ and thus allows estimation of it. The same procedure holds for the intercept constraint matrix $\mathbf{H}_{\Delta t_i}$ which relates the discrete-time intercepts $\mathbf{b}_{\Delta t_i}$ to the continuous time intercepts $\mathbf{b}$ and for the discrete-time intercept covariance matrices $\mathbf{\Phi}_{\kappa_{\Delta t_i}}$ and $\mathbf{\Phi}_{\kappa_{\Delta t_i}, x_{t_0}}$ and their continuous-time analogues. Finally, (6.4) specifies how the discrete-time error covariance matrix $\mathbf{Q}_{\Delta t_i}$ is related to diffusion coefficient matrix $\mathbf{G}$. All expressions in (6.4) are derived in Oud and Jansen (2000) and Singer (1990); see especially Appendix A in the former for the derivation of the integral expressions $\mathbf{H}_{\Delta t_i}$, $\mathbf{b}_{\Delta t_i}$, and $\mathbf{Q}_{\Delta t_i}$.

$$\begin{aligned}
&\mathbf{A}_{\Delta t_i} = \mathrm{e}^{\mathbf{A}\Delta t_i}, \\
&\mathbf{b}_{\Delta t_i} = \mathbf{H}_{\Delta t_i}\mathbf{b} \quad \text{for} \quad \mathbf{H}_{\Delta t_i} = \mathbf{A}^{-1}(\mathbf{A}_{\Delta t_i} - \mathbf{I}), \\
&\boldsymbol{\kappa}_{\Delta t_i} = \mathbf{H}_{\Delta t_i}\boldsymbol{\kappa}, \\
&\qquad \mathbf{\Phi}_{\kappa_{\Delta t_i}} = \mathbf{H}_{\Delta t_i}\mathbf{\Phi}_{\kappa}\mathbf{H}'_{\Delta t_i}, \\
&\qquad \mathbf{\Phi}_{\kappa_{\Delta t_i}, x_{t_0}} = \mathbf{H}_{\Delta t_i}\mathbf{\Phi}_{\kappa, x_{t_0}}, \\
&\mathbf{Q}_{\Delta t_i} = \mathrm{irow}\left[\left(\mathbf{A}\otimes\mathbf{I} + \mathbf{I}\otimes\mathbf{A}\right)^{-1}\left(\mathbf{A}_{\Delta t_i}\otimes\mathbf{A}_{\Delta t_i} - \mathbf{I}\otimes\mathbf{I}\right)\mathrm{row}\left(\mathbf{G}\mathbf{G}'\right)\right].
\end{aligned} \tag{6.4}$$

In addition to the continuous time parameter matrices and the T-1 times repeated discrete time matrices in (6.4), the EDM comprises one more parameter vector and one more parameter matrix for the initial time point t_0, the initial means vector $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$ and initial covariance matrix $\mathbf{\Phi}_{\mathbf{x}_{t_0}}$.

The EDM can be estimated as a structural equation model (SEM). A SEM can be specified in quite different ways and by different numbers of parameter matrices. Here we specify the EDM as a two equations SEM with four parameter matrices: measurement parameter matrices $\mathbf{\Lambda}$ and $\mathbf{\Theta}$, and structural parameter matrices $\mathbf{B}$ and $\mathbf{\Psi}$:

$$\mathbf{y} = \mathbf{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \text{ with } \mathrm{cov}(\boldsymbol{\varepsilon}) = \mathbf{\Theta} \tag{6.5}$$

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\zeta} \text{ with } \mathrm{cov}(\boldsymbol{\zeta}) = \mathbf{\Psi}, \tag{6.6}$$

The model implied moment matrix: $\mathbf{\Sigma}$ = f($\mathbf{\Lambda}$, $\mathbf{\Theta}$, $\mathbf{B}$, $\mathbf{\Psi}$) for the observed variables in $\mathbf{y}$ is a function of the parameter matrices, the likelihood in turn is a function of $\mathbf{\Sigma}$ and sample moment matrix $\mathbf{S}$ such that the maximum likelihood (ML) estimator is obtained by minimizing the discrepancy between $\mathbf{\Sigma}$ and $\mathbf{S}$ in terms of this function. Hence, to obtain the ML estimate of the EDM by means of a SEM program, it suffices to show how the EDM is specified in terms of the SEM parameter matrices $\mathbf{\Lambda}$, $\mathbf{\Theta}$, $\mathbf{B}$, and $\mathbf{\Psi}$.

Oud and Jansen (2000) and Oud and Delsing (2010) describe how the constrained parameter matrices in (6.4) are specified in terms of the SEM matrices. Below we present the specification for the case of three time points ($T = 3: t_0, t_1, t_2$) but this is easily extended to more than four three points. For three time points the vectors **y**, **ε**, **η**, **ζ** in (6.5) and (6.6) are:

$$\mathbf{y} = \begin{pmatrix} \mathbf{y}_{t_0} \\ \mathbf{y}_{t_1} \\ \mathbf{y}_{t_2} \\ 1 \end{pmatrix}, \boldsymbol{\varepsilon} = \begin{pmatrix} \boldsymbol{\varepsilon}_{t_0} \\ \boldsymbol{\varepsilon}_{t_1} \\ \boldsymbol{\varepsilon}_{t_2} \\ 0 \end{pmatrix}, \boldsymbol{\eta} = \begin{pmatrix} \mathbf{x}_{t_0} \\ \mathbf{x}_{t_1} \\ \mathbf{x}_{t_2} \\ 1 \\ \boldsymbol{\kappa} \end{pmatrix}, \boldsymbol{\zeta} = \begin{pmatrix} \mathbf{x}_{t_0} - \boldsymbol{\mu}_{\mathbf{x}_{t_0}} \\ \mathbf{w}_{t_1 - \Delta t_1} \\ \mathbf{w}_{t_2 - \Delta t_2} \\ 0 \\ \mathbf{0} \end{pmatrix}. \tag{6.7}$$

The matrices $\mathbf{B}$, $\mathbf{\Psi}$, $\mathbf{\Lambda}$ and $\mathbf{\Theta}$ are given in (6.8).

6.3 Identification of the EDM/SEM model for four state variables and three time points with equal observation intervals

Identification is an important concern for SEM researchers because the methodology gives users the freedom to specify models that are not identified. Meaningful parameter estimates, however, require the parameters to be at least identified. This is the case, if the unknown parameters can be solved from the data covariance or moment structure. In other words, we must be able to express the parameters as functions of the elements of the observed covariance or moment matrix. In principle, the identification of the measurement model (6.5) and the structural model (6.6) can be intertwined, so that restrictions in one submodel aid identification of the other. However, we will consider identification of the measurement model and structural model separately. So, we will first prove that the measurement model is identified (in terms of $\mathbf{\Sigma}$) and next that the structural model is identified (in terms of latent covariance or moment matrix $\mathbf{\Omega}$) . If both are identified separately, the model as a whole is identified.

We first present the matrices $\mathbf{B}$, $\mathbf{\Psi}$, $\mathbf{\Lambda}$ and $\mathbf{\Theta}$, which for three observation time points are:

$$
\mathbf{B} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{\mu}_{\mathbf{x}_{t_0}} & \mathbf{0} \\ \mathbf{A}_{\Delta t_1} & \mathbf{0} & \mathbf{0} & \mathbf{b}_{\Delta t_1} & \mathbf{H}_{\Delta t_1} \\ \mathbf{0} & \mathbf{A}_{\Delta t_2} & \mathbf{0} & \mathbf{b}_{\Delta t_2} & \mathbf{H}_{\Delta t_2} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix},
$$

$$
\boldsymbol{\Psi} = \begin{pmatrix} \boldsymbol{\Phi}_{\mathbf{x}_{t_0}} & & & & \\ \mathbf{0} & \mathbf{Q}_{\Delta t_1} & & & \\ \mathbf{0} & \mathbf{0} & \mathbf{Q}_{\Delta t_2} & & \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & 1 & \\ \boldsymbol{\Phi}_{\boldsymbol{\kappa},\mathbf{x}_{t_0}} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{\Phi}_{\boldsymbol{\kappa}} \end{pmatrix}, \tag{6.8}
$$

$$
\boldsymbol{\Lambda} = \begin{pmatrix} \mathbf{C} & \mathbf{0} & \mathbf{0} & \mathbf{d} & \mathbf{0} \\ \mathbf{0} & \mathbf{C} & \mathbf{0} & \mathbf{d} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{C} & \mathbf{d} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & 1 & \mathbf{0} \end{pmatrix}, \quad \boldsymbol{\Theta} = \begin{pmatrix} \mathbf{R} & & & \\ \mathbf{0} & \mathbf{R} & & \\ \mathbf{0} & \mathbf{0} & \mathbf{R} & \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & 0 \end{pmatrix}.
$$

For equal observation intervals $\Delta t_1 = \Delta t_2 = \Delta t$ $\mathbf{B}$ and $\boldsymbol{\Psi}$ may also be written

$$
\mathbf{B} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{\mu}_{\mathbf{x}_{t_0}} & \mathbf{0} \\ \mathbf{A}_{\Delta t} & \mathbf{0} & \mathbf{0} & \mathbf{b}_{\Delta t} & \mathbf{I} \\ \mathbf{0} & \mathbf{A}_{\Delta t} & \mathbf{0} & \mathbf{b}_{\Delta t} & \mathbf{I} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix},
$$

$$
\boldsymbol{\Psi} = \begin{pmatrix} \boldsymbol{\Phi}_{\mathbf{x}_{t_0}} & & & & \\ \mathbf{0} & \mathbf{Q}_{\Delta t} & & & \\ \mathbf{0} & \mathbf{0} & \mathbf{Q}_{\Delta t} & & \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & 1 & \\ \boldsymbol{\Phi}_{\kappa_{\Delta t},x_{t_0}} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{\Phi}_{\kappa_{\Delta t}} \end{pmatrix}, \tag{6.9}
$$

in terms of the five EDM discrete time parameter matrices $\mathbf{A}_{\Delta t}$, $\mathbf{b}_{\Delta t}$, $\mathbf{Q}_{\Delta t}$, $\boldsymbol{\Phi}_{\kappa_{\Delta t},x_{t_0}}$, $\boldsymbol{\Phi}_{\kappa_{\Delta t}}$ (see (6.4)) and initial parameter matrices $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$ and $\boldsymbol{\Phi}_{\mathbf{x}_{t_0}}$. It means identification of the structural model part can be done in two steps. We first identify the discrete time parameter matrices and then based on them the corresponding continuous time parameters.

Identification of the measurement model part

We use the quite common assumptions that (1) in the loadings matrix $\mathbf{\Lambda}$ each observed variable is unifactorial (loading on a single latent variable only) (2) $\mathbf{\Theta}$ is diagonal (uncorrelated measurement errors) and (3) each latent variable has at least three observed variables loading on it with one of the three loadings fixed at 1. For $\lambda_1 = 1$, the variances $\sigma_1^2, \sigma_2^2, \sigma_3^2$ and covariances $\sigma_{12}, \sigma_{13}, \sigma_{23}$ of the three variables are:

$$
\begin{aligned}
\sigma_1^2 &= \phi_1 + \vartheta_1, \\
\sigma_2^2 &= \lambda_2^2 \phi_1 + \vartheta_2, \\
\sigma_3^2 &= \lambda_3^2 \phi_1 + \vartheta_3, \\
\sigma_{12} &= \lambda_2 \phi_1, \\
\sigma_{13} &= \lambda_3 \phi_1, \\
\sigma_{23} &= \lambda_2 \lambda_3 \phi_1,
\end{aligned}
\tag{6.10}
$$

with ϕ_1 the variance of the single latent variable, which the three have in common, and $\vartheta_1, \vartheta_2, \vartheta_3$ their measurement error variances. The six unknown parameters in (6.10) are: $\lambda_2, \lambda_3, \phi_1, \vartheta_1, \vartheta_2, \vartheta_3$, which are identified as follows:

$$
\begin{aligned}
\lambda_2 &= \sigma_{23} / \sigma_{13}, \\
\lambda_3 &= \sigma_{23} / \sigma_{12}, \\
\phi_1 &= \sigma_{12} / \lambda_2, \\
\vartheta_1 &= \sigma_1^2 - \phi_1, \\
\vartheta_2 &= \sigma_2^2 - \lambda_2^2 \phi_1, \\
\vartheta_3 &= \sigma_3^2 - \lambda_3^2 \phi_1.
\end{aligned}
\tag{6.11}
$$

The covariances σ_{ij} between the observed variables i and j of different latent variables k and l are written $\sigma_{ij} = \lambda_i \lambda_j \varphi_{kl}$ and so identify the latent covariances $\varphi_{kl} = \sigma_{ij} / (\lambda_i \lambda_j)$.

Consider the case that the measurement equation intercepts are unequal to zero: $\mathbf{d} \neq \mathbf{0}$. Let d_1, d_2, d_3 be the elements of $\mathbf{d}$ in $\mathbf{\Lambda}$ of equation (6.8). Denote the means of the observed variables by μ_1, μ_2, μ_3, and the latent mean by ν_1. Just as it is necessary to restrict one of the loadings, one of the measurement intercepts should be restricted. If we do this by $d_1 = 0$, then, because $\lambda_1 = 1$, the observed means become

$$\begin{aligned}
\mu_1 &= \nu_1, \\
\mu_2 &= \lambda_2 \nu_1 + d_2, \\
\mu_3 &= \lambda_3 \nu_1 + d_3,
\end{aligned} \tag{6.12}$$

and the unknown parameters d_2, d_3, ν_1 are identified as follows:

$$\begin{aligned}
\nu_1 &= \mu_1, \\
d_2 &= \mu_2 - \lambda_2 \nu_1, \\
d_3 &= \mu_3 - \lambda_3 \nu_1.
\end{aligned} \tag{6.13}$$

The latent variances ϕ_k and latent covariances ϕ_{kl} combined with the latent means ν_i define the latent moment matrix $\mathbf{\Omega}$ on which the identification of the structural model is based. So, we will prove next that the parameters of the latent structural model (in $\mathbf{B}, \mathbf{\Psi}$) are functions of the elements in latent moment matrix $\mathbf{\Omega}$ which in their turn are functions of the elements in the observed moment matrix.

Identification of the structural model part

Because identification is done in terms of the latent moment matrix and the measurement model is identified we can assume $\mathbf{\Theta} = \mathbf{0}$ and $\mathbf{\Lambda}$ an identity matrix, except for the last columns (see (6.14)) accommodating the random intercept covariance matrices $\mathbf{\Phi}_{\kappa_{\Delta t}}$ and $\mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}}$.

Because $\mathbf{\Phi}_{\kappa_{\Delta t}}$ and $\mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}}$ specify unobserved heterogeneity in the structural model, they cannot be identified by the measurement model nor considered to be directly part of $\mathbf{\Omega}$, but must be identified as part of the structural model.

As usual in identification proofs, we first derive the moment matrix $\mathbf{\Omega}$ as a function of the parameter matrices $\mathbf{B}$, $\mathbf{\Psi}$, $\mathbf{\Lambda}$, $\mathbf{\Theta}$ (model implied moment matrix), more specifically of the seven unknown parameter matrices: $\mathbf{A}_{\Delta t}$, $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$, $\mathbf{b}_{\Delta t}$, $\mathbf{\Phi}_{\mathbf{x}_{t_0}}$, $\mathbf{Q}_{\Delta t}$, $\mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}}$, $\mathbf{\Phi}_{\kappa_{\Delta t}}$. Next, we analyze the inverse relationships: the parameters as functions of the elements of $\mathbf{\Omega}$.

The model implied moment matrix of a SEM in the four parameter matrices follows from (6.5)-(6.6) and takes the well-known form :

$$\mathbf{\Omega} = \mathbf{\Lambda}(\mathbf{I}-\mathbf{B})^{-1}\mathbf{\Psi}(\mathbf{I}-\mathbf{B}')^{-1}\mathbf{\Lambda}'$$

$$= \begin{pmatrix} \mathbf{M}_1 & & & \\ \mathbf{M}_2 & \mathbf{M}_3 & & \\ \mathbf{M}_4 & \mathbf{M}_5 & \mathbf{M}_6 & \\ \mathbf{M}_7 & \mathbf{M}_8 & \mathbf{M}_9 & 1 \end{pmatrix} \tag{6.14}$$

Matrix $\mathbf{\Omega}$ is partioned into ten submatrices and vectors according to the information given by successive time points: $\mathbf{M}_1$ refers to the initial time point, matrices $\mathbf{M}_2$ and $\mathbf{M}_3$ add information from the second time point, matrices $\mathbf{M}_4$, $\mathbf{M}_5$, and $\mathbf{M}_6$ from the third time point The last row is made up of vectors that exclusively relate to the means: $\mathbf{M}_7$ to the initial means, $\mathbf{M}_8$ the means at the second time point and $\mathbf{M}_9$ the means at the third time point. Not all submatrices are necessary in the context of identification but, as seen in (6.14), for identification information is used form all three time points. It means that for identification of the full structural model at least three observation time points are needed.

Consider (6.15) which shows that the five discrete time parameter matrices $\mathbf{A}_{\Delta t}$, $\mathbf{b}_{\Delta t}$, $\mathbf{Q}_{\Delta t}$, $\mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}}$, $\mathbf{\Phi}_{\kappa_{\Delta t}}$ and the two initial parameter matrices $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$ and $\mathbf{\Phi}_{\mathbf{x}_{t_0}}$ are identified, since all elements can be expressed in terms of elements of $\mathbf{\Omega}$.

$$\begin{aligned}
&\mathbf{M}_7 = \boldsymbol{\mu}'_{\mathbf{x}_{t_0}} && \rightarrow \boldsymbol{\mu}_{\mathbf{x}_{t_0}} = \mathbf{M}'_7 \\
&\mathbf{M}_1 = \mathbf{\Phi}_{\mathbf{x}_{t_0}} + \boldsymbol{\mu}_{\mathbf{x}_{t_0}}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}} && \rightarrow \mathbf{\Phi}_{\mathbf{x}_{t_0}} = \mathbf{M}_1 - \boldsymbol{\mu}_{\mathbf{x}_{t_0}}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}} \\
&\mathbf{M}_2 = \mathbf{A}_{\Delta t}\mathbf{M}_1 + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}} + \mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}} && \\
&\mathbf{M}_4 = \mathbf{A}_{\Delta t}\mathbf{M}_2 + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}} + \mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}} && \\
&\quad \mathbf{M}_4 - \mathbf{M}_2 = \mathbf{A}_{\Delta t}(\mathbf{M}_2 - \mathbf{M}_1) \rightarrow \mathbf{A}_{\Delta t} = (\mathbf{M}_4 - \mathbf{M}_2)(\mathbf{M}_2 - \mathbf{M}_1)^{-1} && \\
&\mathbf{M}_8 = \boldsymbol{\mu}'_{\mathbf{x}_{t_0}}\mathbf{A}'_{\Delta t} + \mathbf{b}'_{\Delta t} && \rightarrow \mathbf{b}_{\Delta t} = (\mathbf{M}_8 - \boldsymbol{\mu}'_{\mathbf{x}_{t_0}}\mathbf{A}'_{\Delta t})' \\
& && \rightarrow \mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}} = \mathbf{M}_2 - (\mathbf{A}_{\Delta t}\mathbf{M}_1 + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}}) \\
&\mathbf{M}_5 = \mathbf{A}_{\Delta t}\mathbf{M}_3 + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}}\mathbf{A}'_{\Delta t} + \mathbf{b}_{\Delta t}\mathbf{b}'_{\Delta t} + \mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}}\mathbf{A}'_{\Delta t} + \mathbf{\Phi}_{\kappa_{\Delta t}} && \\
& && \rightarrow \mathbf{\Phi}_{\kappa_{\Delta t}} = \mathbf{M}_5 - (\mathbf{A}_{\Delta t}\mathbf{M}_3 + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}}\mathbf{A}'_{\Delta t} + \mathbf{b}_{\Delta t}\mathbf{b}'_{\Delta t} + \mathbf{\Phi}_{\kappa_{\Delta t}, x_{t_0}}\mathbf{A}'_{\Delta t})
\end{aligned} \tag{6.15}$$

$$\mathbf{M}_3 = \mathbf{A}_{\Delta t}\mathbf{M}_1\mathbf{A}'_{\Delta t} + \mathbf{A}_{\Delta t}\boldsymbol{\mu}_{\mathbf{x}_{t_0}}\mathbf{b}'_{\Delta t} + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}}\mathbf{A}'_{\Delta t} + \mathbf{b}_{\Delta t}\mathbf{b}'_{\Delta t}$$
$$+ \mathbf{A}_{\Delta t}\boldsymbol{\Phi}'_{\kappa_{\Delta t},x_{t_0}} + \boldsymbol{\Phi}_{\kappa_{\Delta t},x_{t_0}}\mathbf{A}'_{\Delta t} + \boldsymbol{\Phi}_{\kappa_{\Delta t}} + \mathbf{Q}_{\Delta t}$$
$$\rightarrow \mathbf{Q}_{\Delta t} = \mathbf{M}_3 - (\mathbf{A}_{\Delta t}\mathbf{M}_1\mathbf{A}'_{\Delta t} + \mathbf{A}_{\Delta t}\boldsymbol{\mu}_{\mathbf{x}_{t_0}}\mathbf{b}'_{\Delta t} + \mathbf{b}_{\Delta t}\boldsymbol{\mu}'_{\mathbf{x}_{t_0}}\mathbf{A}'_{\Delta t} + \mathbf{b}_{\Delta t}\mathbf{b}'_{\Delta t}$$
$$+ \mathbf{A}_{\Delta t}\boldsymbol{\Phi}'_{\kappa_{\Delta t},x_{t_0}} + \boldsymbol{\Phi}_{\kappa_{\Delta t},x_{t_0}}\mathbf{A}'_{\Delta t} + \boldsymbol{\Phi}_{\kappa_{\Delta t}})$$

Observe that for $\mathbf{A}_{\Delta t}$ to be identified the inverse of $\mathbf{M}_2 - \mathbf{M}_1$ must exist. The elements of $\mathbf{M}_1$ (initial moment matrix) and $\mathbf{M}_2$ allow for this except in exceptional circumstances.

The last step is identification of the five continuous time parameter matrices (see equation (6.4)) on the basis of the five discrete parameter matrices which comes down to application of the constraints in (6.4) in inverse direction. This is straightforward for **b**, $\boldsymbol{\Phi}_{\kappa}$, $\boldsymbol{\Phi}_{\kappa,x_{t_0}}$, and **G**, if the drift matrix **A** is identified on the basis of $\mathbf{A}_{\Delta t}$. A general and efficient procedure to check this is by diagonalization (which is also used in model estimation). The diagonalization procedure requires **A** to have distinct nonzero eigenvalues and nonzero sums of eigenvalue pairs (Oud & Jansen, 2000). This condition is not met in extremely rare cases only. Another nonidentification problem may arise in the case of complex eigenvalues (Singer, 1992), which can be solved by adding additional restrictions.

6.4 Estimation results

Before going into detail, we observe that since this paper is a continuation of Toharudin et al. (2008) which focused on the variables N, I and E, the discussion below will mainly deal with the new variable A. At the end of this section we shall compare the overall results obtained in this paper to those in Toharudin et al. (2008).

By means of Mx the EDM solution for the model with drift matrix (**A**), fixed growth intercepts (**b**), diffusion matrix (**Q**) and initial estimates $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$ and $\boldsymbol{\Phi}_{\mathbf{x}_{t_0}}$ was found. That is, we first excluded trait variables (no $\boldsymbol{\Phi}_{\boldsymbol{\kappa}}$ and $\boldsymbol{\Phi}_{\boldsymbol{\kappa},\mathbf{x}_{t_0}}$) . As the model contains 66 observed variables, the number of nonidentical elements in the (augmented) moment matrix is 0.5 (67 x 68) = 2278. The total number of parameters to be estimated in matrices $\boldsymbol{\Lambda}$ and $\boldsymbol{\Theta}$ of the measurement model (loadings, measurement origins, and measurment error variances) is 70. The number of parameters in **A** is 16, in **b** 4, in **Q** 4 (it was supposed diagonal), in $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$ 4 and in $\boldsymbol{\Phi}_{\mathbf{x}_{t_0}}$ 10. Because also the unit moment in the augmented moment matrix had to be estimated, the total number of parameters estimated is 109 such that the model degrees of freedom df = 2278 − 109 = 2169. The χ^2 = 9487.7 with df = 2169 is not a particularly good fit. It should be noted, however, that this model with 66 observed variables is huge, the sample of N = 1274 is big, and that the time-invariance assumptions put a lot of severe restrictions on the model, especially in the measurement model. Therefore, the popular fit measure RMSEA (Browne and Cudeck, 1993) is often considered to be a more adequate goodness of fit measure. Its value 0.051 indicates that the model fits 'reasonably' well.

Before turning to the estimation results we turn to the measurement of A which is the new element in this chapter. A is measured by the following items (see also Toharudin et al., in press):

No	Items	1991	1995	1999
(1)	Obedience and respect for authority are the two most important virtues children have to learn	X	X	X
(2)	Most of our social problems would be solved, if we could somehow get rid of the immoral, crooked people	X	X	X
(3)	Young people are often rebellious, but they will have to adapt to society as they get older	X	X	
(4)	What we need most, more than laws and institutions, is a few courageous and devoted leaders in whom the people can trust	X	X	
(5)	People can be divided into two distinct classes: the weak and the strong	X	X	
(6)	Everybody would be better off, if people would talk less and work harder	X	X	
(7)	Most people are disappointing, once you get to know them better	X		
(8)	What we need is strong leaders who tell us what to do		X	X
(9)	In every nation there exists a small vanguard of people who lead and a docile mass of people who follow			X

As can be seen in **Table 6.1**, item (1) has loading λ_1 = 1.000. Since a loading λ_i is directly related to the true score variance of a variable (= observed variance − measurement error variance), all other items have lower true score variance than item (1). If the true score variance of item (1) is ϕ_1, the true score variances of the other items are $\lambda_i^2\phi_1$. Items (4) and (9) have lowest loadings and thus lowest true score variances. This is reflected in the reliabilities, which are lowest for these items (0.241 and 0.236, respectively), whereas the reliability of item (1) is highest (0.528).

Table 6.1 displays the loadings, measurement origins and measurement error variances for all four latent variables and z-values which show that all measurement parameters are highly significant.

We now turn to the structural model presented in **Table 6.2**. Most important is the drift matrix **A** which shows that like I, N, and E, A has a significant negative auto-effect (−0.065), implying stability or a long term tendency for the individual A trajectories to converge to the mean trajectory. Observe that the auto-effect of −0.065 is close to 0, meaning that the persistence of an authoritarian attitude over time is extremely strong.

Table 6.1 Loadings (unstandardized), measurement origins, measurement error variances, and reliabilites (R^2) for the items of the latent variables (z-values italic)

Latent Variable	Individualism (I)	Nationalism (N)		Authoritarianism (A)		Ethnocentrism (E)
Loadings						
Item (1)	1.000	0.324		1.000		1.000
	-	*29.230*		-		-
Item (2)	0.766	1.000		0.822		1.069
	35.243	-		*28.316*		*40.110*
Item (3)	0.767	0.329		0.713	(1991/1995)	1.071
	33.401	*30.443*		*28.057*		*39.343*
Item (4)	0.634	0.495	(1991)	0.669	(1991/1995)	1.214
	33.014	*27.087*		*22.468*		*41.403*
		0.288	(1995/1999)			
		26.803				
Item (5)				0.924	(1991/1995)	0.965
				26.912		*34.258*
Item (6)				0.906	(1991/1995)	0.813
				25.457		*32.527*
Item (7)				0.748	(1991)	1.250
				17.805		*41.791*
Item (8)				0.978	(1995/1999)	1.218
				27.716		*38.841*
Item (9)				0.695	(1999)	
				15.955		
Measurement Origins						
Item (1)	1.000	0.286		1.000		1.000
	-	*5.344*		-		-
Item (2)	0.364	1.000		0.188		-0.369
	6.569	-		*1.680*		*-4.666*
Item (3)	0.415	0.871		0.944	(1991/1995)	-0.216
	7.100	*16.793*		*9.594*		*-2.675*
Item (4)	0.608	0.163	(1991)	1.260	(1991/1995)	-0.154
	12.424	*1.925*		*10.929*		*-1.768*
		1.824	(1995/1999)			
		34.272				
Item (5)				-0.321	(1991/1995)	0.183
				-2.416		*2.191*
Item (6)				-0.437	(1991/1995)	0.249
				-3.177		*3.360*
Item (7)				-0.018	(1991)	-0.584
				-0.112		*-6.582*
Item (8)				-1.044	(1995/1999)	-0.477
				-7.725		*-5.133*
Item (9)				0.436	(1999)	
				2.621		

Table 6.1 (Continue)

Latent Variable	Individualism (I)	Nationalism (N)		Authoritarianism (A)		Ethnocentrism (E)
Measurement Error Variances						
Item (1)	0.581	1.371		0.501		0.726
	29.827	*38.986*		*33.488*		*40.723*
	R^2=0.599	R^2=0.288		R^2=0.528		R^2=0.417
Item (2)	0.657	3.813		0.780		0.443
	36.893	*27.328*		*39.377*		*38.166*
	R^2=0.352	R^2=0.640		R^2=0.331		R^2=0.558
Item (3)	0.749	1.129		0.489	(1991/1995)	0.510
	37.598	*37.231*		*32.305*		*38.882*
	R^2=0.472	R^2=0.351		R^2=0.390		R^2=0.532
Item (4)	0.553	1.127	(1991)	0.729	(1991/1995)	0.447
	37.966	*18.198*		*33.589*		*36.629*
	R^2=0.346	R^2=0.567		R^2=0.241		R^2=0.639
		0.751	(1995/1999)			
		30.329				
		R^2=0.364				
Item (5)				0.780	(1991)	0.727
				22.827		*40.916*
				R^2=0.274		R^2=0.429
Item (6)				0.839	(1991/1995)	0.640
				32.250		*41.461*
				R^2=0.372		R^2=0.307
Item (7)				0.891	(1991/1995)	0.455
				32.331		*36.359*
				R^2=0.329		R^2=0.643
Item (8)				0.701	(1995/1999)	0.661
				30.333		*39.005*
				R^2=0.368		R^2=0.555
Item (9)				0.709	(1999)	
				22.513		
				R^2=0.236		

This negative auto-effect for A together with the other effects in drift matrix $\mathbf{A}$ gives an autoregression for A over the 4-year period between waves of not less than 0.780, which is slightly higher than in the other state variables E, I and N.

The autoregression matrix $\mathbf{A}_{\Delta t} = e^{\mathbf{A}\Delta t}$ in Table 6.3 is computed by means of diagonalization: $e^{\mathbf{A}\Delta t} = \mathbf{M}e^{\mathbf{V}\Delta t}\mathbf{M}^{-1}$ ($\mathbf{M}$ eigenvector matrix and $\mathbf{V}$ diagonal eigenvalue matrix of A). The autoregression matrix matrix shows that all four variables have a strong tendency to persist over time, but that this tendency is particularly strong for A. Next we turn to the cross-effects.

Figure 6.1 shows the standardized cross-effects. It shows a clear and relatively strong feedback relationship between A and E. The standardized effect from A to E is 0.039, the highest cross-effect in the model; from E to A it is 0.031, the next highest in the model. Both effects are highly significant. In addition, A has a relatively strong effect on I but there is no reverse effect from I to A. Note also that N is slightly, but significantly, influenced by I and E but not by A. Indirectly A has effects on N via E and I, but these will be extremely small. It follows that Flemish nationalism is a somewhat independent phenomenon in Belgian politics that is barely influenced by an authoritarian attitude and only feebly by the ethnocentric and individualistic standpoints often ascribed to the voters of the Vlaams Blok. E takes the most central position in the structure, since it has feedback relationships with A and I, and unidirectionally influences N.

Table 6.2 EDM Estimates by means of Mx (in A, b, and Q; z-values italic); the values in A have been standardized

$$\mathbf{A} = \begin{array}{c} \\ \mathrm{I} \\ \\ \mathrm{N} \\ \\ \mathrm{A} \\ \\ \mathrm{E} \\ \\ \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{I} & \mathrm{N} & \mathrm{A} & \mathrm{E} \end{array} \\ \begin{bmatrix} -0.080 & -0.004 & 0.029 & 0.021 \\ \mathit{-9.51} & \mathit{-0.81} & \mathit{3.82} & \mathit{2.96} \\ 0.016 & -0.063 & -0.010 & 0.016 \\ \mathit{2.54} & \mathit{-10.24} & \mathit{-1.49} & \mathit{2.55} \\ 0.008 & -0.008 & -0.065 & 0.031 \\ \mathit{1.34} & \mathit{-1.58} & \mathit{-8.40} & \mathit{4.89} \\ 0.031 & 0.007 & 0.039 & -0.082 \\ \mathit{5.43} & \mathit{1.67} & \mathit{6.22} & \mathit{-12.72} \end{bmatrix} \end{array}$$

$$\mathbf{b} = \begin{array}{c} \mathrm{I} \\ \\ \mathrm{N} \\ \\ \mathrm{A} \\ \\ \mathrm{E} \\ \\ \end{array} \begin{bmatrix} -0.013 \\ \mathit{-0.499} \\ 0.179 \\ \mathit{2.69} \\ 0.142 \\ \mathit{6.60} \\ 0.018 \\ \mathit{0.996} \end{bmatrix}$$

$$\mathbf{Q} = \mathbf{GG}' = \begin{array}{c} \\ \mathrm{I} \\ \\ \mathrm{N} \\ \\ \mathrm{A} \\ \\ \mathrm{E} \\ \\ \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{I} & \mathrm{N} & \mathrm{A} & \mathrm{E} \end{array} \\ \begin{bmatrix} 0.081 & & & \\ \mathit{10.59} & & & \\ & 0.474 & & \\ & \mathit{10.72} & & \\ & & 0.031 & \\ & & \mathit{9.07} & \\ & & & 0.047 \\ & & & \mathit{14.60} \end{bmatrix} \end{array}$$

Although the z-test, which comes down to dividing the parameter estimate by its standard error, and the calculation of confidence intervals around the parameter estimate by means of the standard error are very popular procedures, they have been criticized.

The authors of Mx (Neale et al , 2004, p. 94) rightly observe that the z-test is not invariant under transformation of the statistic. For instance, the test of, say parameter a^2, does not give the same result as the direct test of a . A well-known example is testing the variance σ^2, leading to a z-value that is only half the z-value of σ and so to accepting the nullhypothesis in many cases where this would not be the case for σ.

Mx offers an alternative to the z-test and z-based confidence intervals in the form of the likelihood-ratio test and likelihood-based confidence intervals. The latter are obtained by determining the critical parameter values below and above the estimated parameter value through repeated Mx analyses, yielding the appropriate χ^2-differences (difference in χ^2-value for the estimated parameter value and the upper or lower value). It is well-known that the χ^2-difference of nested models is itself χ^2-distributed and as a test statistic equivalent to the likelihood-ratio of the nested models.

Because the importance of the cross-effects in matrix **A** is crucial for the causal structure depicted in **Figure 6.1**, we computed the likelihood-based confidence intervals for all 12 cross-effects. The results are given in **Table 6.4**. As pointed out by Neale et al. (2004, p. 95), the optimization procedure in the Mx program to calculate confidence interval limits does not always give reliable results, in which cases warnings are given by the program. Unreliable limits are left blank in **Table 6.3**. Only for two of the 12 coefficients (a_{32} and a_{41}) limits were lacking which made it impossible to compare the 5%-level significance z-test results in **Table 6.2** with corresponding likelihood-based test results in **Table 6.3**. (Observe that the lack of upper limits for a_{42} and a_{43} does not invalidate the conclusion that these variables are significant because the estimate and the lower limit are positive.) In two cases (a_{12} and a_{42}) the likelihood-based results indicated significance, whereas the z-test results did not. However, even if significant, the original as well as the standardized coefficients are so small, that they have to be interpreted as virtually zero. In one case (a_{14}) the z-test results indicated significance, whereas the likelihood-based test did not. Because of the relatively high standardized value of 0.021 of the effect of E on I, we used the z-test as decision criterion and decided to consider the effect to be significant. However, even excluding this effect would not basically modify the causal picture in **Figure 6.1**.

Table 6.3 Autoregression matrix $A\Delta t$ based on drift matrix A in Table 6.1 for Δt=4

$$\begin{array}{c} \\ \text{I} \\ \text{N} \\ \text{A} \\ \text{E} \end{array}\begin{array}{c} \begin{array}{cccc} \text{I} & \text{N} & \text{A} & \text{E} \end{array} \\ \begin{bmatrix} 0.732 & -0.014 & 0.093 & 0.067 \\ 0.050 & 0.779 & -0.025 & 0.049 \\ 0.030 & -0.022 & 0.780 & 0.094 \\ 0.092 & 0.020 & 0.123 & 0.732 \end{bmatrix} \end{array}$$

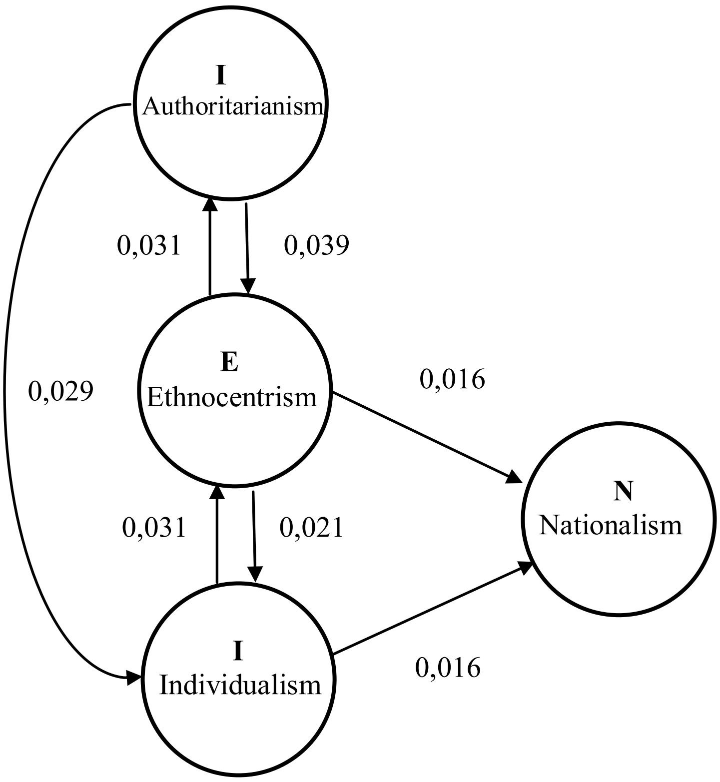

Figure 6.1 Dynamic relationships between latent state variables Authoritarianism (A), Ethnocentrism (E), Individualism (I), and Nationalism (N); only significant effects are included and standardized coefficients reported

After estimating the relatively simple model with only state variables, we next analyzed whether a model including the trait variables would lead to an improvement. For that purpose we specified in $\mathbf{\Phi}_{\kappa}$ the four trait variances on the diagonal and in $\mathbf{\Phi}_{\kappa,x_{t_0}}$ the four trait-state covariances on the diagonal. Although the model fit as measured by χ^2 improved ($\chi^2 = 9241.2$ with $df = 2161$), there was no improvement in RMSEA, however. In addition, there were negative trait variances for I and E, an unduly large trait variance of 780.6 for N and a negligeable trait variance of 0.00050 for A. As for the model with only I, N, and E in Toharudin (2008), we therefore conclude that no trait variables need to be specified and that the initial covariance matrix $\mathbf{\Phi}_{\mathbf{x}_{t_0}}$ (Table 6.5 which also includes the initital mean vector) is sufficient to differentiate trajectories of individual subjects from the mean trajectory.

Table 6.4 95% likelihood-based confidence intervals for the cross-coefficients in A, computed by Mx; unstandardized estimates

Coefficient	Estimate	Lower limit	Upper limit
a_{12}	-0.0016	-0.0022	-0.0015
a_{13}	0.0357	0.0178	0.0594
a_{14}	0.0267	-0.0379	0.0447
a_{21}	0.0432	0.0432	0.0767
a_{23}	-0.0342	-0.0791	0.0092
a_{24}	0.0562	0.0133	0.0991
a_{31}	0.0067	-0.0029	0.0165
a_{32}	-0.0022	-0.0029	
a_{34}	0.0319	0.0195	0.0449
a_{41}	0.0247		0.0336
a_{42}	0.0022	0.0019	
a_{43}	0.0386	0.0190	

Table 6.5 Mx estimates of $\mathbf{\Phi}_{\mathbf{x}_{t_0}}$ and $\boldsymbol{\mu}_{\mathbf{x}_{t_0}}$

$$
\begin{array}{c} \\ \mathrm{I} \\ \\ \mathrm{N} \\ \\ \mathrm{A} \\ \\ \mathrm{E} \\ \end{array}
\begin{array}{c}
\begin{array}{cccc} \mathrm{I} & \mathrm{N} & \mathrm{A} & \mathrm{E} \end{array} \\
\begin{bmatrix}
0.791 & & & \\
\mathit{16.56} & & & \\
-0.179 & 6.015 & & \\
\mathit{-2.33} & \mathit{16.54} & & \\
0.334 & -0.177 & 0.527 & \\
\mathit{12.97} & \mathit{-2.85} & \mathit{16.18} & \\
0.322 & 0.108 & 0.29016 & 0.506 \\
\mathit{13.29} & \mathit{1.90} & \mathit{14.21} & \mathit{17.10}
\end{bmatrix} \\
\mathbf{\Phi}_{\mathbf{x}_{t_0}}
\end{array}
\qquad
\begin{array}{c} \mathrm{I} \\ \\ \mathrm{N} \\ \\ \mathrm{A} \\ \\ \mathrm{E} \\ \end{array}
\begin{array}{c}
\begin{bmatrix}
2.450 \\ \mathit{82.22} \\ 4.232 \\ \mathit{50.47} \\ 3.831 \\ \mathit{150.58} \\ 2.947 \\ \mathit{116.85}
\end{bmatrix} \\
\boldsymbol{\mu}_{\mathbf{x}_{t_0}}
\end{array}
$$

6.5 Autoregression functions, cross-lagged effect functions, and latent mean trajectory estimates and predictions

The autoregression and cross-lagged effect functions, computed by means of the matrix exponential $\mathbf{A}_{\Delta t} = \mathrm{e}^{\mathbf{A}\Delta t}$ (see the first autonomous part in equation (6.3)-(6.4)), trace the effect of a unit increase in each of the four state variables on themselves and on each other over intervals of arbitrary length Δt. As the coefficients in $\mathbf{A}_{\Delta t}$ are standardized in terms of the initial standard deviations, both the autoregression functions in **Figure 6.2** and the cross-lagged effect functions in **Figure 6.3** give the effect in terms of a standard deviation unit increase in the dependent variable resulting from one standard deviation increase in the causal variable at the initial time point. We will concentrate on the autoregression function and cross-lagged effect functions involving the new variable A and pay attention to the other autoregression and cross-lagged effect functions mainly, if the results differ from those reported in Toharudin et al. (2008).

We first discuss the autoregression functions. An autoregression function describes the autonomous development of a variable, showing which proportion of its value at the start is likely to persists over time.The autoregression functions in **Figure 6.2** show that all four variables have a strong tendency to persist over time. The tendency is strongest, however, for the new variable A: the autoregression function predicts that after 12.4 years still 50% of the initial A value is left. After 40 years still 19% is left compared to 15% in E, 10% in I and only 8% in N. In fact, autoregression is everywhere highest for A.

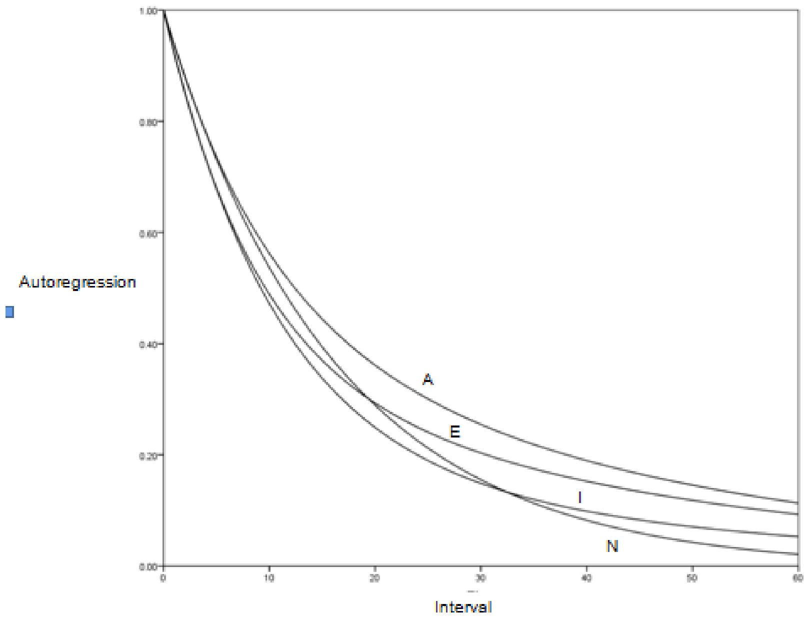

Figure 6.2 Autoregression Functions

Toharudin et al. (2008) pointed out that the autoregression functions of I, E and N are non-monotonous in the sense that the relative positions of I, E and N differ for different intervals. This present study shows this even more clearly. Responsible for the non-monotonicity is the autocorrelation function of N, which in the beginning is as persistent as A but crosses E after 19.5 years and I after 32 years. It means that Flemish nationalism initially is rather persistent but after approximately a decade decreases more quickly than E and I. Observe that this finding of crossing autoregression functions stresses the necessity of continuous time analysis. Discrete time analysis would for an observation interval of, for instance, 19.5 or more have led to different conclusions about the relative order of the autoregressions than for smaller intervals.

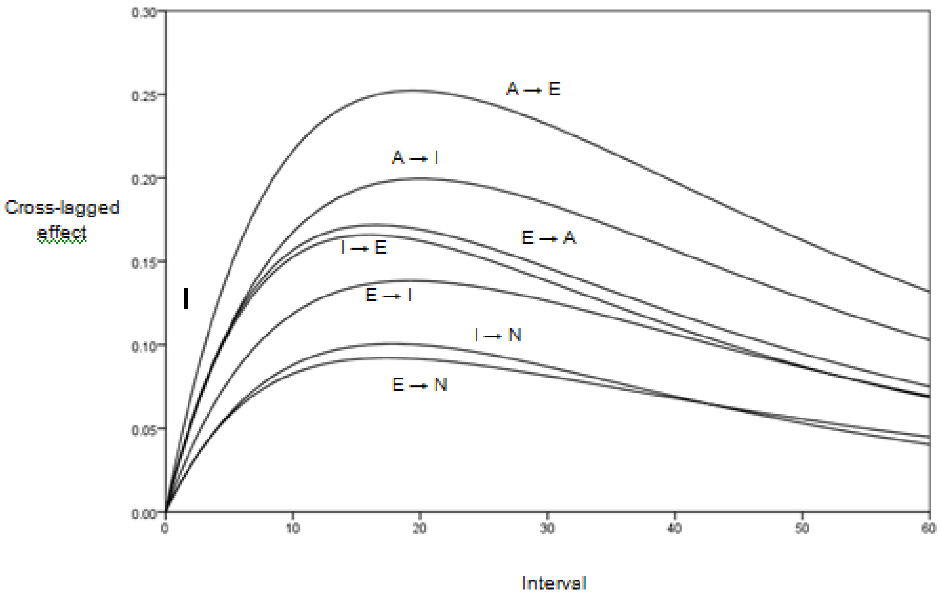

Figure 6.3 Cross-lagged effect functions for the significant cross-effects in Table 6.2

Figure 6.3 shows that the three cross-lagged effect functions involving A everywhere exceed the four other cross-lagged effect functions. The two reciprocal cross-lagged effect functions A → E and E → A reach their maximum standardized values of 0.25 and 0.17 after 19.6 and 16.4 years, respectively. The maximum of A → I of 0.20 is reached after approximately 20 years. It should be noted that the four other cross-lagged effect functions are similar to the ones in Toharudin et al. (2008) but have lower maxima. Moreover, I → N and

E → N cross after 42.6 years and I → E and E → I after 53.4 years. However, these conclusions need to be interpreted with greatest prudence because of the extremely long intervals after which the crossings show up.

Figure 6.4 displays the mean trajectories of the four variables, computed until 2051. For I, N, and E the means hardly differ from the ones in Toharudin et al. (2010): N increases in the data collection period (1991-1999), and is predicted to increase for some time afterwards but levels off at the end of the prediction period (1999-2051), whereas the means of the other variables hardly change. Also the mean of A hardly changes: a tiny drop from 3.83 to 3.78 during the data collection period, followed by a further slight drop to 3.62 over the prediction period.

We now turn to the question whether the results with regard to I, N, and E, reported in Toharudin et al. (2008), remain valid after the introduction of A into the model. Most of results with regard of I, N, and E are close to those in Toharudin et al. (2008) in spite of the introduction of A, the use of ADM instead of the EDM, and the fact that one of the items used to measure I in Toharudin et al. (2008) was dropped. This conclusion applies to the measurment model as well as to the structural model. It is highly remarkable that even the standard errors and therefore the z-values do not differ much from those in Toharudin et al. (2008). The main differences are found with respect to the latent growth intercepts **b** (see **Table 6.2**), especially with regard to I and E. The reason could be that these variables undergo significant influences from A with A's specific mean influencing the intercepts and that one of the previous items is lacking in I which influences the mean of I and therefore also its intercept.

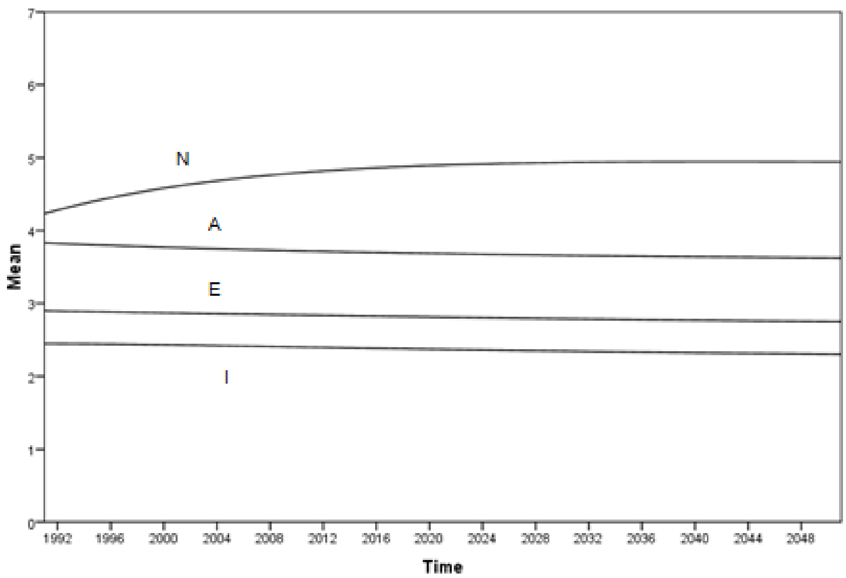

Figure 6.4 Latent mean estimates and predictions over 1991-2051

6.6 Conclusions

Nationalism (N), Ethnocentrism (E), Individualism (I), and Authoritarianism (A) in Flanders have been the subject of several studies before, but a longitudinal analysis has not been performed on all four concepts simultaneously nor have their relationships and the direction of their relationships been studied in continuous time. In this paper a simultaneous continous time state-space analysis is performed of all four concepts.

We proved identification of all parameters in the SEM-EDM model with three time points and used the Mx-program for estimation purposes. The result above show the dynamic relationships between the latent state variables individualism, nationalism, authoritarianism, and ethnocentrism. The estimated model differs from the hypothesized model in that nationalism is found to have no significant influence on authoritarianism, and that there is a reciprocal relationship between ethnocentrism and authoritarianism.

The autoregression functions show that all four variables have a strong tendency to persist over time. It means that people who have a high or low level of I, N, A, or E tend to keep that level over quite a long period of time. Moreover, the three cross-lagged effect functions involving A exceed the four other cross-lagged effect functions everywhere. The mean trajectories of the four variables are computed until 2051. For I, N, and E the means hardly differ from the ones in Toharudin et al. (2010): N increases in the data collection period (1991-1999), is predicted to increase for some time afterwards too but levels off at the end of the prediction period (1999-2051). The means of the other variables hardly change.

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